CRIMINOLOGY

THE COMPANY YOU KEEP? THE SPILLOVER EFFECTS OF GANG MEMBERSHIP ON INDIVIDUAL GUNSHOT VICTIMIZATION IN A CO-OFFENDING NETWORK*

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The effects of gang membership on individual social, behavior, cognitive, and health outcomes are well documented. Yet, research consistently has shown that gang membership and the boundaries of gangs are often fluid and amorphous. The current study examines how social proximity to a gang member in one's co-offending network influences the probability of being a gunshot victim. We re-create and analyze the social network of all individuals who were arrested, summonsed for a quality-of-life violation, and subjected to noncustodial police contacts in Newark, New Jersey, during a 1-year time period (N = 10,531). A descriptive network analysis finds an extreme concentration of fatal and nonfatal gunshot injuries within a small social network: Nearly one third of all shootings in Newark occur in a network that contains less than 4 percent of the city's total population. Furthermore, a series of logistic regression models finds that being directly or indirectly linked to a gang member in one's co-offending network has a significant effect on one's probability of being a gunshot victim. Implications of these findings for the study of gangs, gun violence, and a public health approach to violence are discussed.

On a brisk October day in 2014, "Greg," a 24-year-old Black male member of the G-Shine Bloods, and "Tony," a 23-year-old Black male nongang associate, were standing in front of a carwash near Spencer Street and Alexander Street in the Vailsburg neighborhood of Newark, New Jersey.[1] A blue BMW with tinted windows containing members

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1. We have changed the names of the participants and some of the details of this incident to ensure anonymity.

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of the 793 Bloods, who are rivals of the G-Shines, cruised down Spencer Street and pulled over not far from where Greg and Tony were standing. At least one member of the 793 Bloods leaned through the window with a .40-caliber handgun and opened fire on Greg and Tony, wounding both men nonfatally in their legs. Although the exact motive of the shooting is unclear, police believe it was related to an ongoing drug-turf–related dispute between the G-Shines and 793 Bloods.

The shooting of a gang member by another gang member is a frequent occurrence in many U.S. cities; research has underscored that gang membership is strongly associated with heightened levels of violent victimization (Peterson, Taylor, and Esbensen, 2004; Pyrooz, Moule, and Decker, 2014; Thornberry, 1998). Regardless of the particular situation, gang membership seems to carry with it elevated risks derived from group processes within the gang, gang lifestyle and behaviors, or simply the aggregation of high-risk individuals who join such groups (see Thornberry et al., 2003, for a summary of this debate). Greg's victimization fits exactly such an academic—and often policy—narrative of a victim whose gang membership enhanced his probability of getting shot.

But, how do we explain Tony's victimization? If one considers the boundaries of the G-Shines to be a rigid wall demarking member from nonmember, then Tony would be a "bystander" or "third party" to the event that was driven by a gang-level dispute—an individual whose routine activities placed him in a risky situation and thus exposed him to gang violence (see Spano, Freilich, and Bolland, 2008). Tony's connection to G-Shine was secondary, and he was not (to the best of anyone's knowledge) involved in the dispute that led to the shooting. Tony just happened to be with Greg that day. At the same time, however, Tony was directly linked to Greg who *was* a member of G-Shine. In fact, Tony was stopped by the police *with* Greg just a month before the shooting. This connection gives Tony an *indirect* connection to G-Shine through his past (potentially criminal) association with Greg. Perhaps in this situation, the known effects of gang membership associated with Greg extended to Tony indirectly through their criminal connection. Stated more generally, maybe the known risks associated with gang membership can extend beyond individual gang members to affect others in their social networks.

The current study attempts to answer this question by examining how social proximity to a gang member in one's co-offending network—literally, how close one is to a gang member—relates to the probability of being a gunshot victim. Gun violence itself tends to concentrate within small networks, and recent studies have begun to uncover the effect of the placement of individuals within such networks on the probability of being a victim (Papachristos, Braga, and Hureau, 2012; Papachristos and Wildeman, 2014). This study extends this scholarship by assessing how the presence of another risk factor—in this case, gang membership—might also affect victimization. As in the case of Tony and Greg, we hypothesize that the negative effects of gang membership can and do reach beyond gang members to include others to whom they are connected. We maintain that such effects would be especially acute within behavioral and association networks, such as co-offending networks, that heighten potential exposure not only to risky individuals but also to risky situations and encounters.

We test this hypothesis by re-creating and analyzing the co-offending networks among all individuals who were arrested, summonsed for quality-of-life violations, and subjected to noncustodial police contacts in the City of Newark during a 1-year time period. Descriptive network analysis finds an extreme concentration of fatal and nonfatal gunshot injuries within co-offending networks in Newark: Nearly one third of all fatal and

nonfatal shootings occur in a network that contains less than 4 percent of the city's total population. Furthermore, a series of logistic regression models finds that being close to a gang member in one's co-offending network has a significant effect on one's probability of being a gunshot victim.

This article proceeds by reviewing the research on the effects of gang membership. Next, we discuss how conceiving of street gangs as networks can aid in our understanding and measurement of the effects of gang membership beyond those individuals identified as gang members. We then provide a descriptive analysis of shootings in Newark as well as the co-offending network. Finally, we present the results from our regression analyses that test our central hypotheses.

EFFECTS OF GANG MEMBERSHIP

Gang membership is associated with a host of negative social, behavioral, cognitive, and health outcomes, including increased self-reported and police-recorded crime and delinquency (Battin et al., 1998); higher rates of violent offending and victimization (Peterson, Taylor, and Esbensen, 2004; Pyrooz, Moule, and Decker, 2014; Thornberry, 1998); higher levels of drug selling and use (Esbensen and Huizinga, 1993; Fagan, 1989); higher rates of school dropout and lower academic performance (Pyrooz, 2014); higher rates of incarceration (Gilman, Hill, and Hawkins, 2014); and overall poor social, emotional, and mental health (Gilman, Hill, and Hawkins, 2014; Harper and Robinson, 1999). Debate exists as to whether such negative outcomes are related to *selection* into gangs or the *facilitation* of such behaviors by group processes (Gordon et al., 2004; Thornberry et al., 2003). Cohort studies tend to support the facilitation effect by demonstrating that negative behaviors are heightened during periods of active gang membership and that such effects are robust across a variety of individual, familial, and community risk factors (Thornberry et al., 2003). Yet the dearth of longitudinal data continues to raise a call for a better understanding of the causal nature of this relationship.

Although most surveys tend to measure gang membership as a dichotomous variable (one is or is not a gang member) or as a categorical variable summarizing an individual's status in the gang (core, peripheral, semiperipheral, etc.), qualitative and longitudinal research consistently reminds us that gang membership is a fluid and dynamic process that vacillates over the life course. Individuals flow in and out of periods of "active" gang membership as they go about their lives. Individuals move into and out of gang membership during bouts of incarceration, sporadic periods of employment and schooling, or as their romantic relationships ebb and flow (Decker, 1996; Fleisher, 1998; Thornberry et al., 2003). By drawing on social network theory, Pyrooz, Sweeten, and Piquero (2013) called for a deeper understanding of "gang embeddedness," the extent of an individual's immersion, involvement, and identification within the gang and how such embeddedness influences individual outcomes and find that less embedded members are more likely to leave the gang earlier in their delinquent careers.

The boundaries of gangs themselves can also be quite amorphous as qualitative and ethnographic studies frequently describe how gangs often spill over into nongang friendship, kinship, and neighborhood networks. Fleisher (1998), for example, described how the lives of young women who are not themselves officially "members" of the Fremont Hustlers are intertwined with the lives of gang boys and, as a result, are at times just as volatile or dangerous. Garot's (2010) study of school youth in California and Harding's

(2010) study of adolescents in Boston detailed numerous ways that nongang youth get entangled in social webs of gang members simply because of friendships or neighborhood affiliation—nongang youth are caught in the "drama" of the street simply because they go to school, live next to, hang out with, or are related to gang-involved youth.

Just as gang interpersonal and social connections extend beyond the boundaries of gang membership, so do criminal and delinquent connections of gang members. For example, Morselli's (2009) analysis of the drug-dealing activities of the Bo-Gars gang in Montreal found that only 23 of the 70 individuals in the network (approximately 32 percent) were members of the gang; in this case, the criminal activities of Bo-Gars extended beyond their gang associates to include nongang co-offenders as well. Other network studies by Bouchard and Konarksi (2014), Fleisher (2006), and Papachristos, Braga, and Hureau (2012) underscored this point by documenting co-offending patterns of gang members that extend beyond gang boundaries and, in some cases, even connect gangs thought to be rivals.

The theme of this line of research follows a consistent logic: Gangs, as groups, and gang members, as individuals, are not partitioned off from their communities, socially or criminally. The lives of gang members are woven into the larger social fabric of their neighborhoods, social networks, families, and friends. Gang members can and often do engage in criminal and delinquent activities with individuals not associated with their gang. Although research has documented the effects of gang membership on those who join gangs and is beginning to explore how embeddedness in the gang might condition such effects, research has rarely considered how the effects of gang membership might spill over from the gang or gang members to other people in their immediate networks. If gang membership increases one's probability of being a victim of a violent crime and if the boundaries of gang membership are fluid, then we hypothesize that the effects of gang membership might extend to those individuals directly and indirectly connected to gangs or gang members through co-involvement in risky behaviors. To link back to the shooting that introduced this article: Did the co-offending connection between Tony and Greg increase Tony's likelihood of being a gunshot victim? We examine this hypothesis by analyzing how social proximity to a gang member in a co-offending network impacts the probability of being a gunshot victim.

NETWORK ANALYSIS AND EXPOSURE TO GANG MEMBERS

Understanding how the effects of gang membership might spill over from individual gang members to their associates requires thinking about gangs not as monolithic and impervious organizations but as social networks. Social network analysis (hereafter, simply SNA) refers to both a theoretical perspective and a set of methodological techniques. Theoretically, SNA refers to the study of the way actors are connected and how such interdependencies affect what we feel, think, and do (for a recent review, see Kadushin, 2012). For the network analyst, the people we marry, the votes we cast, and the diseases we catch are all influenced by the connections around us and our placement in such networks. Methodologically, SNA refers to a catalog of statistical techniques based on mathematical graph theory.

A "social network" is measured as a set of relationships on a bounded set of actors (Wasserman and Faust, 1994). "Actors," in this networked sense, can be individuals, organizations, websites, cities, or any meaningful social unit of interest that can have

relationships defined among its population. “Relationships” can refer to any type of tie, association, or link between units—e.g., friendship ties, trading patterns, advice seeking, sexual relationships, money transfers, co-membership, and so on. In graph theoretical terms, a network consists of 1) a set of vertices that represent a bounded set of actors and 2) a set of lines or edges that define the relationships among them (Wasserman and Faust, 1994). Visually, a network (or graph) is depicted in such a way that the vertices are represented as a series of nodes and the edges as lines connecting the nodes.

Many of criminology’s central theories implicitly or explicitly invoke the *idea* of social networks. To give just two examples, differential association theory posits the central role of peer networks in processes of social learning necessary to participate in crime and delinquency (Haynie, 2001; Matsueda, 1982; Sutherland, 1947), and social control and collective efficacy theory highlight the importance of neighboring networks in the activation or mobilization of resident ties to mitigate deviant behavior (Bursik, 1999; Sampson, 2012). Although these two theories are interested in different types of networks—differential association on the peer networks of the delinquents and social control/collective efficacy theory on the networks of neighborhood residents—each considers the shape, structure, and contours of networks an important factor in shaping the nature of the crime problem. Despite such long-held importance of networks in criminological theory, the application of formal network methods and models is still in its infancy, and the “coming of a networked criminology” has only just begun (Papachristos, 2011).

The study of street gangs is one area within criminology that has seen a steady application and extension of SNA in recent years (see Sierra-Arevalo and Papachristos, 2015). Despite long-standing debates about what defines a gang, gangs are first and foremost groups and, as some have argued, social networks (Fleisher, 2006; Papachristos, 2006). Gang members are tied to one another through membership to a common group, as well as through neighborhood, school, friendship, and familial ties. Applying SNA to the study of street gangs thus affords a unique opportunity to analyze—rather than assume—the structure of gangs and then to correlate how the observed networks and network positions can influence individual or group behaviors (see Morselli, 2009).

Recent applications of SNA have yielded important insights into the network structure of gangs. In one of the first formal applications of SNA to gangs, McGloin (2005) found that gangs in Newark, New Jersey, were not hierarchical organizations but, instead, were largely disorganized networks with smaller pockets of activity and cohesion. Fleisher (2006), in a study of gang girls in Champaign, Illinois, demonstrated how interpersonal and friendship ties cut across gang affiliation, even among gangs with long-standing disputes and rivalries. By using historical data from the 1960s, Hughes (2013) found that gangs in Chicago with lower levels of network cohesion also had lower levels of violence and that boys occupying prestigious positions in a gang were at increased risk for violent victimization. In a study of one high-crime Boston community, Papachristos, Braga, and Hureau (2012) created a single network of 763 gang and nongang members that included more than eight unique gangs directly or indirectly connected to each other through the criminal behaviors of their members and nongang associates.

Studies such as these have confirmed the fluid nature of gang boundaries and, perhaps more importantly, have provided a way to measure the overlap and integration of gang networks into larger nongang networks. Given these findings, we hypothesize that the negative effects of gang membership might also reach into larger social networks. Our hypothesis parallels theories of “social contagion” in network science that

believe that one's own opinions, behaviors, and attitudes are influenced by those in one's network (Burt, 1987; Marsden and Friedkin, 1993). Research across the social, behavioral, and medical sciences has demonstrated how behaviors and outcomes such as obesity (Christakis and Fowler, 2007), happiness (Fowler and Christakis, 2008), depression (Rosenquist, Fowler, and Christakis, 2011), substance abuse (adams, Moody, and Morris, 2013; Koester, Glanz, and Baron, 2005; Kreager, Rulison, and Moody, 2011), and even delinquency can diffuse through social networks (Haynie, 2001).

Understanding and measuring how the effects of gang membership might diffuse through a network requires specification of the types of ties, relationships, and behaviors conducive to social contagion. As discussed, a multitude of such ties might connect gang members to each other and nongang associates, including friendship, familial, membership, neighborhood, or co-offending ties. To date, network research on gangs has focused on several of these tie types typically for single gangs (e.g., Bouchard and Konarski, 2014; Morselli, 2009), geographic communities (e.g., Fleisher, 2006), or cities (Kennedy, Braga, and Piehl, 1997; McGloin, 2005). Only a handful of studies have examined multiple types of ties across gang members simultaneously (e.g., Fleisher, 2006; Malm, Bichler, and Van De Walle, 2010) or cross-gang ties of any kind (e.g., Fleisher, 2006; McGloin, 2005; Papachristos, Braga, and Hureau, 2012).

In the current study, we focus on a single type of tie that we posit is conducive to the contagion of gun violence and the potential effects of gang membership: *co-offending*. Co-offending is conducive to social contagion for at least three reasons. First, co-offending has been well documented in a vast body of criminological research as being an important base for many of the group processes at the heart of crime and violence and that the size, shape, and structure of co-offending networks is related to a wide range of criminal outcomes and trajectories (see Warr, 2002, for a detailed review). Recently, McGloin and Nguyen (2014) argued the formal analysis of co-offending networks might shed light on some of criminology's central theoretical concepts (Morselli, 2009; Papachristos, 2011). Second, by virtue of their group nature, gangs may amplify group processes and delinquency simply by expanding one's accessible pool of potential co-offenders (e.g., Hughes 2013). In other words, gangs may provide potentially willing co-offenders in ways that nongang peer groups or friendship cliques might not.

Finally, unlike survey data on friendship nominations that capture an individual's preferences or nominations, co-offending data represent an observation of a specific behavior that prior research has demonstrated elevates one's risk of subsequent crime and violence. A small but growing body of research analyzing co-offending networks provides some initial evidence for this assumption. Research by Papachristos and colleagues studied all fatal and nonfatal gunshot injuries in a high-crime Boston community (Papachristos, Braga, and Hureau, 2012) and all gun homicides in a high-crime Chicago community (Papachristos and Wildeman, 2014) to analyze the role co-offending networks play in individual gunshot victimization. These studies found that gunshot injuries were concentrated within co-offending networks. For example, in the Boston study (Papachristos, Braga, and Hureau, 2012), 85 percent of all gunshot victims were in a single network of less than 5 percent of the community's population, whereas 40 percent of all gun homicides in Chicago occurred in a network of less than 4 percent of the study community's population. These studies also found that the proximity to shooting victims in one's network was directly related to one's own probability of being a victim, above and beyond individual risk factors, including gang membership. Both of these findings

imply an important relationship between co-offending networks and the risk of gunshot injuries.

Focusing on co-offending networks and gangs requires some clarification as to what we are and are not studying. As stated, co-offending networks are behavioral networks. Co-offending networks thus tell us something about the activity and behaviors of gang members, but they say little about the formal or informal leadership or organizational structures of gangs, which might also exert an influence on crime and delinquency (e.g., Decker, Katz, and Webb, 2007). As such, co-offending networks more accurately represent *behavioral* networks—like needle-sharing or sexual networks (e.g., Bearman, Moody, and Stovel, 2004; Koester, Glanz, and Baron, 2005)—that capture a specific event but produce larger network patterns that—again like needle-sharing or sexual networks—might influence social contagion processes. Likewise, it should be recognized that co-offending networks are a subset of a much larger social network in which gang members exist. Although co-offending networks overlap with larger social networks (see McGloin and Nguyen, 2014) and it is probably safe to assume that co-offenders "know each other" beyond the co-offending event, such information is not available in our data. Last, our current data fail to capture networks that might amplify or mute the effects of co-offending networks—e.g., familial, employment, or school networks. These limitations notwithstanding, the focus on co-offending networks for an entire city offers a promising avenue of inquiry into a much larger criminological phenomena (the study of co-offending) as well as a way to analyze specific group effects (gang membership) and criminal behaviors (gun violence).

CURRENT STUDY

The current study combines these recent insights from network science and the research on street gangs to understand how, if at all, the effects of gang membership might spill outward from gang members to nongang members in their co-offending networks. As such, this study advances criminological thinking on networks, gangs, and the study of gun violence more broadly in several key ways. First, we advance the study of gun violence by analyzing how the patterns of fatal and nonfatal gunshot injuries are situated within a network for an entire city, Newark, New Jersey. To date, research has considered either snowball samples for a select population (Papachristos, Braga, and Hureau, 2012) or the network for a single community (Papachristos and Wildeman, 2014). These prior studies, thus, have captured largely homogenous populations whereby the current study's focus on the network for an entire city captures considerably more variation at the individual level known to be associated with victimization.

Second, this study combines prior findings on street gangs with developments in SNA to understand how an important outcome—in this case, gunshot victimization—might be influenced by the shape of networks. Given the relationship between homicide and violent crime and overall life expectancy and health in minority populations (Harper et al., 2007), understanding how networks influence gun violence might provide insight into a significant health problem. Finally, whereas prior network research in criminology has focused primarily on friendship nominations from surveys (Haynie, 2001; Kreager, Rulison, and Moody, 2011; Payne and Cornwell, 2007), our study builds on the small but growing number of studies analyzing co-offending networks (McGloin and Piquero, 2010; Papachristos

and Wildeman, 2014) by drawing on multiple sources of police-recorded information that broaden the potential scope of our co-offending and criminal network.

Our study has two empirical objectives. First, we will analyze the distribution of fatal and nonfatal gunshot injuries for the entire city of Newark in order to assess how victims cluster within co-offending networks. Doing so also permits us to analyze how risk assessment varies not only by traditional risk factors like age, race, and gang membership but also by network status and position. Our second objective, testing our hypothesis regarding distance to gang members, is possible only after having first created the co-offending networks of individuals and situating gunshot victims and gang members within it.

NATURE OF FATAL AND NONFATAL GUN VIOLENCE IN NEWARK, NEW JERSEY

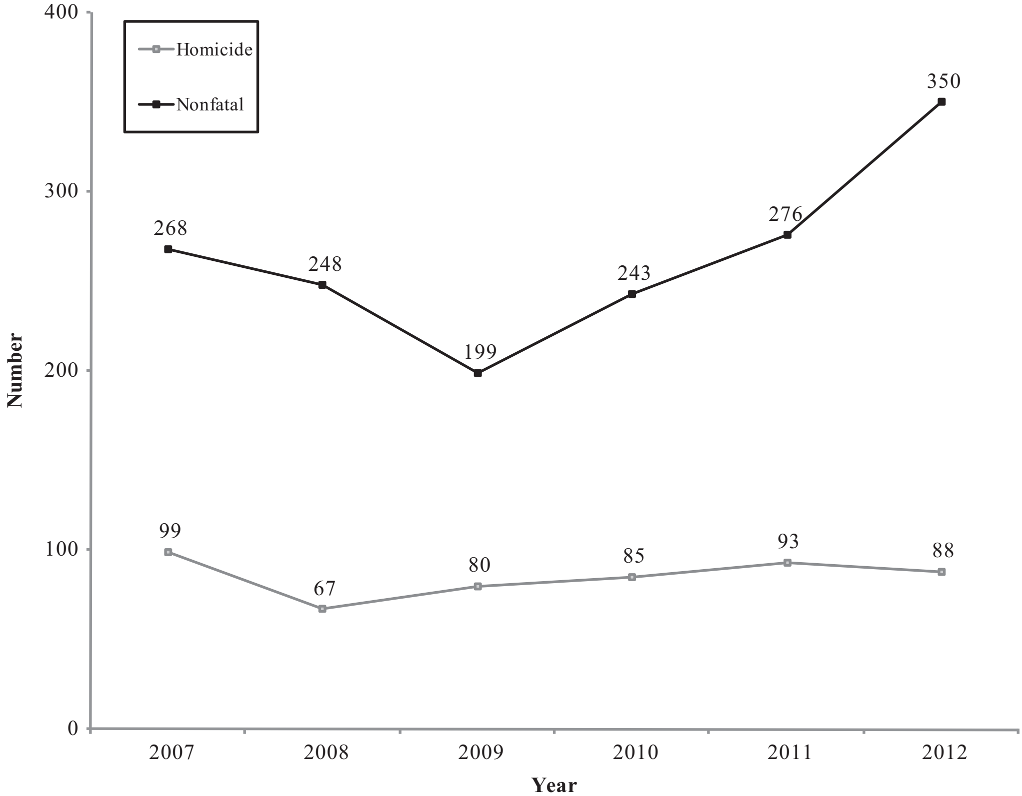
Newark is the largest city in the state of New Jersey with 277,140 residents in 2010 and has long held a reputation as one of the more violent cities in the United States (U.S. Census Bureau, 2015). According to the U.S. Department of Justice (2012), in 2012, Newark had a total violent index crime rate of 1,154.5 and a homicide rate of 34.4 per 100,000 residents—a homicide rate more than seven times higher than the national rate of 4.8 per 100,000 residents. Figure 1 presents the yearly number of murders and nonfatal shooting victimizations in Newark between 2007 and 2012.[2] During this time period, Newark averaged approximately 85 murders per year with a near-linear increase from 67 murders in 2008 to 93 murders in 2011. There were 88 murder victims in 2012, which was a slight decline from the previous year. The number of nonfatal shooting victimizations decreased by 25.7 percent from 268 victims in 2007 to 199 victims in 2009, but since then, it has climbed steadily to a high of 350 victims in 2012, representing a 75.8 percent increase over the 2009 level of victimization.

Previous research has underscored the importance of gang-related violence as a driver of homicide and gun violence in Newark. Between 1999 and 2004, Pizarro and McGloin (2006) attributed more than one third of 417 homicides to gang-related motives. Relative to non–gang-related homicides, gang-related homicides in Newark were significantly more likely to be committed with guns, to occur outdoors, to involve multiple suspects, and to entail victims and offenders who were well known to the criminal justice system. Pizarro and McGloin (2006) also noted that gang homicides were more likely than nongang homicides to be precipitated by microlevel group processes such as escalating dynamics set in motion by threats and culminating in violence or retaliation (see also Decker, 1996).

McGloin (2005) suggested that the gang violence problem in Newark revolved around four primary street gangs—Bloods, Crips, Latin Kings, and Ñetas. Similar to other cities, the Bloods and Crips in Newark represent larger gang conglomerates composed of a variety of smaller "sets" as opposed to a single "corporate-style" entity, which is an organizational pattern described by Decker (1996) as "constellation" gangs. Newark gangs are

2. The Newark Police Department (NPD) defines nonfatal shooting incidents as gun assault events involving the discharge of a firearm where at least one victim is nonfatally wounded by the fired bullet. Nonfatal shooting incidents can involve multiple victims. NPD tracks the total yearly number of nonfatal shooting victimizations as its key measure of nonfatal assault gun violence in the city.

Figure 1. Number of Nonfatal Shootings and Murders, 2007 to 2012

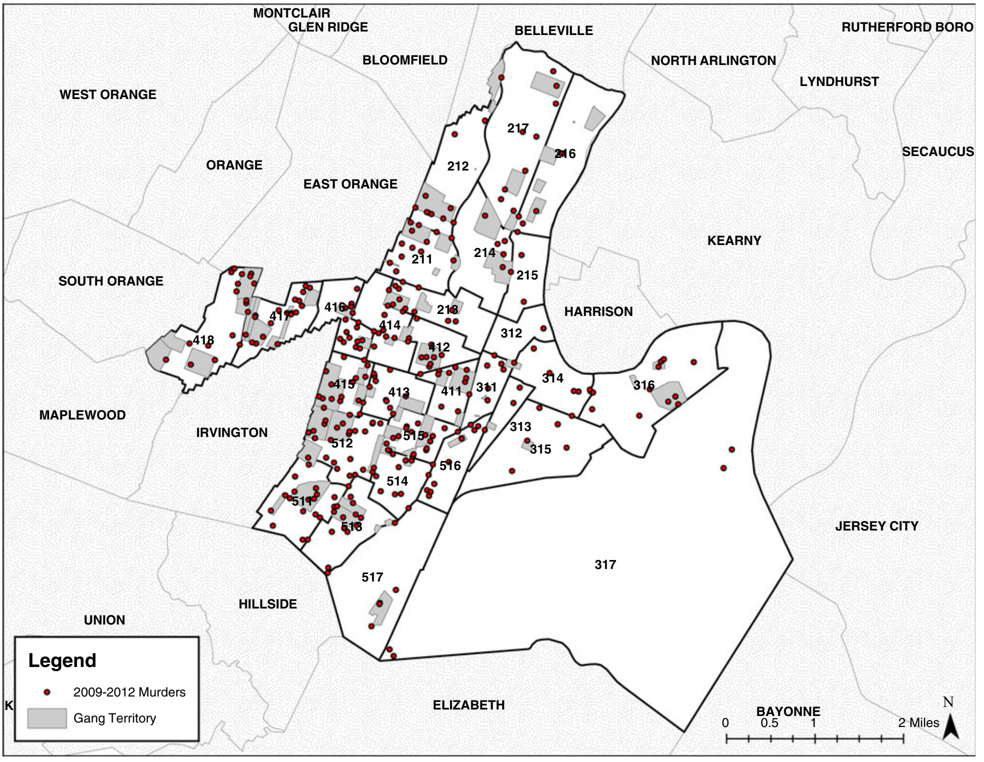


generally disorganized and loosely connected but with identified pockets of cohesive subgroups within gang networks and with particular individuals that were deeply embedded in their respective networks (McGloin, 2005). Importantly, McGloin (2005) suggested that these cohesive subsets had individual allegiances that spanned multiple gangs and were not necessarily reflective of homogeneous gang sets—preliminary evidence that the boundaries of Newark gangs, like those in other cities, are amorphous.

More recently, Zeoli et al. (2014) examined the spatial and temporal movement of 2,366 homicide incidents in Newark from January 1982 through September 2008. Zeoli et al. (2014) found considerable evidence that the diffusion of violence in Newark followed epidemic-like patterns; specifically, spatial clusters of firearm and gang homicide evolved from a common area in the center of Newark and spread southward and westward over the course of two decades with gangs and firearms serving as the infectious agents or point sources of diffusions. The spread of gangs and gang conflicts into vulnerable, disadvantaged neighborhoods over time was identified as an important source of the spatial diffusion of homicide across Newark.

Figure 2 presents a map of murders in Newark between 2009 and 2012, and it shows the spatial distribution of Newark gang turf areas in 2011. Systematic mapping of gang turf areas revealed that Newark gangs were spread throughout the city with particular turfs

Figure 2. Spatial Distribution of 2009–2012 Murders (N = 346) and Gang Turfs (N = 73) in Newark



experiencing higher levels of murders than other turfs.[3] These 73 areas included some 88 sets of 19 distinct Newark gangs. Bloods (a constellation gang with subsets such as 793, Sex Money Murder, Piru, and Brick City Brims), Crips (a constellation gang with subsets such as Grape Street and Hoover), and Latin Kings were the most prevalent gang affiliations across these gang turf areas. Although ongoing conflicts among Newark gangs do occur, NPD gang officers described most homicides involving gang members as involving drug and personal disputes rather than deep-rooted group-level conflicts.

Table 1 presents the circumstances of Newark murders between 2009 and 2012 categorized by both motive and the percent of each category of motive in which a gang member was involved.[4] Overall, whereas gang-related motives—those incidents in which the homicide itself was *directly* motivated by a gang-level dispute—accounted for only

3. Data were collected during the problem analysis phase of the implementation of the Newark Violence Reduction Initiative focused deterrence strategy. The gang mapping exercise described by Kennedy, Braga, and Piehl (1997) was replicated in Newark by using knowledgeable NPD detectives and officers from each precinct and from the gang, drug, violent crime, and intelligence units to map gang turf areas.

4. Murder circumstance data were drawn from the Newark Violence Reduction Initiative problem analysis research and were collected by using a "crime incident review" process (see Klofas and Hipple, 2006). Briefly, this process involved the collection of detailed qualitative data on the

Table 1. Circumstances of and Gang Member Involvement in Newark Murders, 2009–2012

Circumstance	Total *N*	Percent Murder	Percent Gang Member Involved
Drug-related violence	113	32.7	60.9
Arguments or personal disputes	84	23.7	62.9
Gang-related violence	50	16.3	100.0
Robbery	42	14.5	48.1
Domestic or family violence	25	7.2	17.3
Other	9	2.6	16.6
Unknown	23	6.6	33.3
Total	346	100.0	59.5

16.3 percent of the total homicides, gang *members* were involved in roughly 60 percent of all homicides during the observation period. For instance, nearly 61 percent of drug-related disputes, 63 percent of personal disputes, and 48 percent of street robberies involved known gang members.

Taken together, past research and contemporary descriptive data underscore the importance of gangs in Newark murders and nonfatal shootings. Virtually all corners of the city are somehow touched by gang territory, and most murder incidents involve a member of a gang if only as a participant in the event.

(RE)CREATING THE CO-OFFENDING NETWORK

We created the co-offending network in Newark by linking individuals through joint participation in NPD arrest records, field interrogation (FI) reports, and quality-of-life (QOL) summons for the 1-year period between July 1, 2010 and June 30, 2011. Our approach is similar to that used in recent network research that employed police records to determine network ties between two individuals (McGloin and Piquero, 2010; Papachristos and Wildeman, 2014). The usual caveats associated with the use of official police data in criminological research circumscribe the data we used to construct Newark's criminal network, such as bias introduced by police decision-making processes (see Black, 1970).

The NPD arrest database tracks specific charges associated with arrested individuals, uses unique identifiers for specific arrested individuals (as well as their names and dates of birth [DOBs]), and contains information on the type of offense, date and time of the arrest, location of the arrest, and unique arrest record number. During the study time period, the NPD made 19,752 arrests involving some 38,295 criminal charges. The NPD requires its officers to complete FI reports when they perform pedestrian or traffic stops of individuals. FI reports include a narrative description of the legal justification for the stop as well as the date, time, and location of the stop, and the names and DOBs of all individuals involved. Between July 1, 2010 and June 30, 2011, the NPD completed 7,418 FI reports. Finally, the NPD routinely issues QOL summons to individuals engaged in

motives and individuals involved in Newark murder incidents. Review participants included homicide detectives and gang unit officers. They shared their working knowledge on circumstances of the shooting event, relationships between victims and suspects, and for events involving gang members, details on the gangs involved in the shooting.

disorderly behavior that violates city ordinances. The NPD issued 23,364 QOL summons during the study time period. QOL data contain information on the types of ordinance violations; unique identifiers for the individuals cited (names and DOBs); and the date, time, and location of the violations.

Re-creating these networks entailed a two-step process: first, identifying all unique individuals in the data and, second, establishing all instances in which two or more individuals were reported together in the same event. We establish a tie between two individuals when they are listed as joint participants in an event—e.g., co-offenders on an arrest, co-cited individuals on a QOL summons, or observed associating together in an FI contact. The resulting two-mode network represents joint participation in such an event—essentially a person-by-event matrix (Wasserman and Faust, 1994).

The second step entails converting this two-mode person-by-event matrix to a one-mode person-by-person matrix by multiplying the two-mode matrix by the transpose of itself.[5] Although the tie is created through a particular observation at a particular point in time—the date of the police-recorded event—the tie probably existed before the event; that is, individuals more likely than not knew each other *prior* to their co-offending. Importantly, creating networks in this way produces a conservative measure of an individual's network because these data include only those activities known to the police, which resulted in the police taking some sort of action. Individuals clearly have more associates (criminal or otherwise) whom the police do not observe in their custodial and noncustodial contacts with individuals on the streets of Newark.

Based on these procedures, we identified 10,731 unique individuals in the data who had at least one tie to another individual representing *nearly 4 percent of the city's total population of 277,410 residents in 2010*. Isolates, individuals whom we identified in the data without any ties, are excluded from the current analysis because they are not part of a network component (technically, each isolate represents its own component), and as such, their "closeness" to any other person cannot be quantified. Individuals in these data were mainly male (81 percent) and African American (70 percent) with an average age of approximately 36 years. After running the names and DOBs of individuals in the co-offending network through the NPD gang database, we documented that approximately 7 percent of the individuals in the sample ($n = 751$) were police-identified gang members.[6]

In total, we identified 12,736 unique ties linking these individuals through arrest, FI, or QOL records. Approximately 35.6 percent of all individuals in the network had at least one arrest tie, 34.9 percent had a QOL tie, and 57.2 percent had an FI tie. Twenty percent of individuals had more than one tie type, whereas only 3 percent had all three types of ties.

The total network created through these methods contains 10,731 individuals and 12,736 ties. The total network is composed of 2,941 unique components (or subgraphs of the network in which each included node can be reached directly or indirectly) ranging from a size of 2 (individuals with a tie to only a single other person) to a size of 1,807 (a component in which each of these 1,807 individuals is connected directly or indirectly).

5. All analyses were conducted by using the igraph library (Csardi and Nepusz, 2006) in the statistical program, R (R Core Team, 2014).

6. When classifying individuals as confirmed gang members, the NPD follows state of New Jersey gang member criteria outlined in Title 2C of New Jersey statues except for individuals who self-admit to being a gang member (National Gang Center, n.d.).

The size of these components is skewed. Nineteen percent of all individuals are in components of size two (dyads), whereas 65 percent are in components ranging from size 3 to 68. Approximately 17 percent of the sample is in a single large connected component.

On average, any individual in our sample is connected to approximately 2.37 other individuals. However, as in other social networks including co-offending networks, the degree distribution (the distribution of people in terms of how many ties they have) is highly skewed. Most individuals in our network have only a single tie—hence the large number of dyads—whereas a small number of individuals have greater than five ties.

Members of 19 unique gangs were located in the data, representing all identified gangs in Newark. Eighteen of these gangs are located in the largest component, highlighting that members of gang sets are connected to each other outside of the boundaries of their groups, sometimes *indirectly* through associates in their networks. In addition, the presence of a large number of gangs in the largest component also means potentially high levels of exposure to gang members for others in the network.

Finally, gunshot victimization is highly concentrated *within* the network: Only 84 of the 2,941 network components (2.8 percent) have at least one fatal or nonfatal shooting in the observation period. These network components contain only 2,635 individuals—roughly 25 percent of the total network population and less than 1 percent of the city's total population.

METHODS

Official shooting victimization records were used to create our dependent variable, a binary indicator of whether any individual in the network was a victim of a fatal or nonfatal gunshot injury (1 = yes, 0 = no) between July 1, 2010 and June 30, 2011 ($N = 383$ total Newark shooting victims during the observation period). We confirmed individuals in the network were bona fide shooting victims by matching their names and DOBs to the shooting database.

With respect to our second objective, we employ a series of logistic regression models of the probability of whether an individual is a gunshot victim on a series of control variables and parameters for network structure and exposure. In its most basic form, our model takes the form:

$$ln\left(\frac{p_{\mathrm{i}}}{1-p_{\mathrm{i}}}\right) = \mathrm{a} + \beta_{(\text{age})} + \beta_{(\text{race})} + \beta_{(\text{sex})} + \beta_{(\text{gang member})} + \beta_{(\text{degree})} + \beta_{(\text{ego}-\text{density})} + \beta_{(\text{closeness to gang member in network})} + \epsilon$$

where p_{i} is the probability that an individual is a victim of a homicide and the β's represent the effect of variables described in table 2. All models include control variables for mean-centered age (in years), gender (male = 1, female = 0), whether the individual is Black (1 = yes, 0 = no), and whether the individual is a gang member (1 = yes, no = 0).

Models also include three variables to capture important features of the co-offending network: degree centrality, ego-network density, and cluster size. In the current study, we use *degree centrality* to count the total number of ties any individual node has to other individuals in a network (Wasserman and Faust, 1994). The properties of degree centrality are often associated with power, influence, and popularity (Wasserman and Faust, 1994).

Table 2. Network Descriptive Statistics (N = 10,731)

Variables	Mean	SD
Percent Black	.703	.455
Percent male	.810	.391
Percent gang members	.067	.256
Age (in years)	36.130	12.340
Degree (*N* of ties)	2.370	2.350
Ego-network density	.395	.463
Closeness to gang	.181	.328

In epidemiological research, a high degree is often associated with greater infectivity or susceptibility in that high-degree individuals have greater levels of exposure to different sources of infection (Valente, 2010). Because inclusion in the network required at least one co-offending incident, degree centrality in our study captures the number of unique co-offenses in which any individual was involved during the study period. This captures both a sense of co-offending history as well as an overall sense of exposure to a greater range of risky individuals, situations, and behaviors.

We could not acquire prior arrest histories for individuals who appeared in the co-offending network based on connections established through FI report data only. Unfortunately, FI data lack unique NPD arrested offender identification numbers required to make exact links to NPD arrest data. Developing a database programming solution or conducting manual searches of NPD databases required resources that went far beyond the scope of this inquiry. As such, we could not include a direct measure of individual criminal propensity into our models.

Ego-network *density* refers to the overall connectedness of an individual's immediate network—the proportion of possible ties in a person's network that are in fact present (Marsden, 2002).[7] The density of a network ranges from zero (no nodes are connected) to one (all nodes are connected to each other). Put another way, ego-network density captures the extent to which any individual's associates are also associates with each other; a dense ego network means that an individual's associates are also associates, whereas a less dense network means that an individual's associates most likely belong to different social circles.

Cluster size is measured simply as the total number of individuals within each individual's respective network component. Given the distribution of cluster size, this variable acts as an important control in our statistical models.

CLOSENESS TO GANG MEMBERS

The central hypothesis of this study is that being close to gang members in one's network increases the likelihood of victimization through a process of social exposure: If

7. Formally, ego-network density is measured as: $\Delta = \frac{\sum_{i,\ j=1}^{n} x_{ij}}{(\frac{n(n-1)}{2})}$ where n is the number of nodes in the network and $\sum_{i,\ j=1}^{n} x_{ij}$ is the sum of all ties in the network. One is subtracted from n because we are not interested in self-ties, and this factor is divided by 2 because the ties are nondirectional. Therefore, we only consider half of the socio-matrix (Marsden, 2002). In the case of ego-network density, the focal node is removed when calculating its density. Individuals with only a single tie are given a density of zero.

gang members are at elevated risk of victimization, then being associated with a gang member carries with it an elevated risk through a process of *indirect* exposure. Following prior social network research (Christakis and Fowler, 2007, 2008) and recent extensions in criminology (Papachristos, Braga, and Hureau, 2012), we measure such exposure as the "closeness" of any individual in the network to a gang member within his or her respective network component.[8] This measure was calculated through a two-step process.

First, we measure the minimum "social distance" of each individual to a gang member within his or her respective component, in this case, the *geodesic distance* between an individual and a gang member. Each tie removed from an individual equates with a distance of 1 or, informally, one "handshake" away from the focal actor. The geodesic distance refers to the shortest path between two nodes, n_i and n_j, where the distance is simply $d_{(i,\,j)}$. The shortest distance is the smallest value of $d_{(i,\,j)}$. A geodesic of 1 means that the closest gang member is an immediate associate, a geodesic of 2 means the closest gang member is an associate's associate, and so on. Because individuals can be connected in multiple ways to multiple gang members, we captured the *minimum geodesic distance to a gang member*.

To create our *closeness* metric, we then calculated 1 divided by the minimum geodesic distance for each person in the network. This step was taken for two important reasons. First, the distance between disconnected components is infinity. Moving infinity to the denominator creates a metric in which "zero" closeness becomes analytically meaningful—i.e., either the absence of a gang member in one's own component or the lack of a connection to a component with a gang member. Second, measuring closeness in this way also produces a comparable metric across components of vastly different sizes.

Measured in this way, the closeness to gang member metric ranges from zero (no connection to a gang member) to one (immediately connected to a gang member). The average closeness to a gang member is .182; however, the standard deviation of .328 indicates high variability in closeness to gang member across the network.

RESULTS

RISK OF HOMICIDE AND NONFATAL GUNSHOT INJURY

Table 3 presents a summary of the distribution of fatal and nonfatal gunshot victims throughout the entire city as well as within the co-offending network. The final column of table 3 provides the city totals when subtracting those shootings that occur within the network.

Overall, 287 nonfatal and 96 fatal shootings occurred in Newark during the observation period, which is a total rate of 138 per 100,000. As shown in the second column of table 3, approximately 36 percent of all nonfatal shootings and 24 percent of all homicides occurred within the network. Put another way, *approximately 33 percent of all shootings occurred in network components comprising approximately less than 4 percent of the entire population of Newark.*

8. We are grateful to the editor for the thoughtful suggestion on modifying our original distance measure.

Table 3. Fatal and Nonfatal Shootings in the Observed Network and in Newark

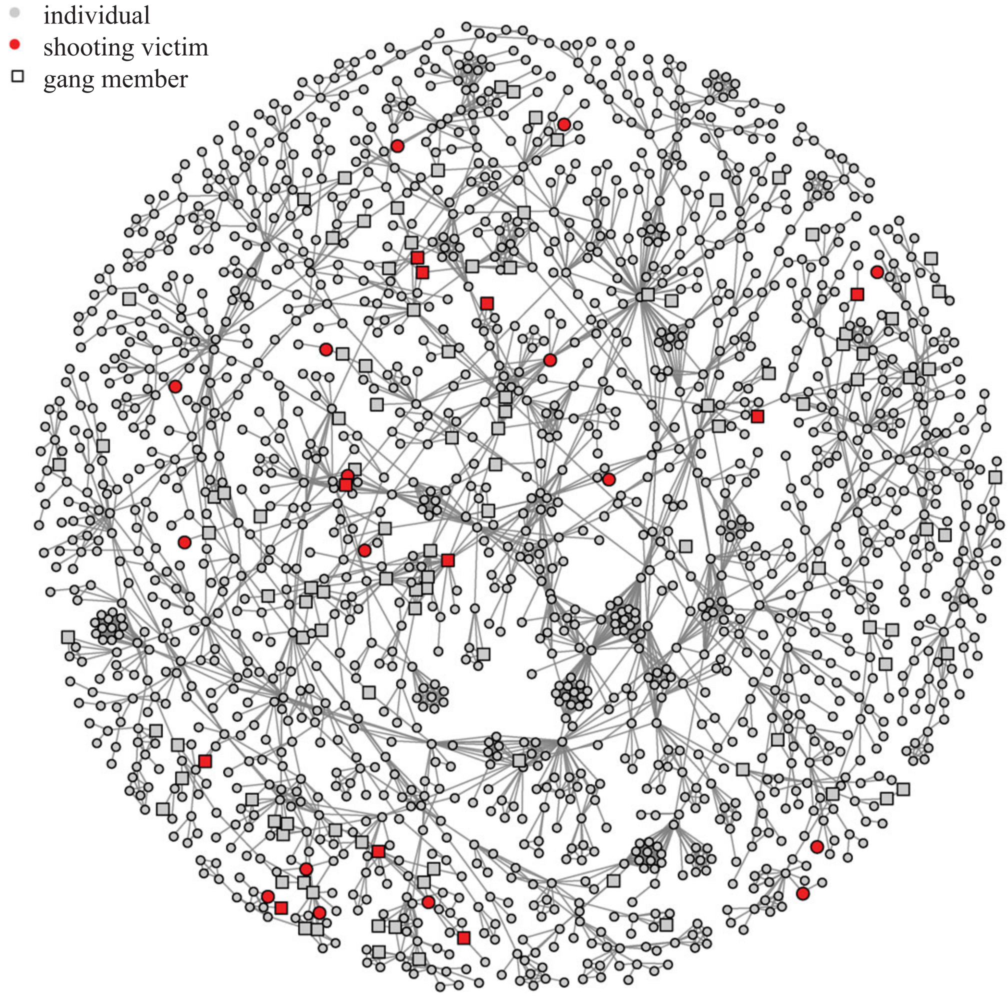
Variables	Newark	Observed Network	Newark – Observed Network
Total population	277,540	10,731	266,809
Percent of total population	100%	4%	96%
N nonfatal shootings	287	102	185
Percent of total nonfatal shootings	100%	36%	64%
Rate per 100,000	103	951	69
N fatal shootings	96	23	73
Percent of total fatal shootings	100%	24%	76%
Rate per 100,000	35	214	27
N total shootings	383	125	258
Percent of total shootings	100%	33%	67%
Rate per 100,000	138	1165	97

This concentration of shootings with this network has two important consequences on how we understand the risk of victimization in Newark: It drives up the rate of victimization within the network while driving down the overall citywide rate of victimization for those outside the network. As shown in the second column of table 3, the rate of nonfatal shooting victimization for those *inside* the network skyrockets from the citywide estimate of 103.4 per 100,000 to 950.51 per 100,000—a staggering 822 percent difference and a figure approximately consistent with similar concentration observed in Chicago co-offending networks (Papachristos and Wildeman, 2014). Conversely, the citywide rate for those not in the network (last column) drops to 69.3 per 100,000, which is still an exceptionally high rate but is approximately 33 percent lower than the overall city rate. The risk of homicide victimization shows a similar pattern as the rate for those inside the network jumps from 34.6 per 100,000 to 214.3 per 100,000 while dropping to 27.4 per 100,000 for those not in the network. Strikingly, the overall rate of victimization for either nonfatal or fatal gunshot injury in the network is 1,164.8 per 100,000; this rate is more than 743 percent higher than the citywide rate.

This concentration of shootings within the observed network, however, obscures the fact that these events are further concentrated *within* the network. That is, even within the high-risk population represented in these data, violence tends to concentrate within various parts of the network. To illustrate this point, figure 3 focuses on the largest component in the network and plots the victims of fatal and nonfatal shootings. Each node in figure 3 represents a unique individual in the data, and each edge represents at least one connection between an individual. The larger darker (shown in red in the online version) nodes represent victims of nonfatal and fatal shootings; squares represent police-identified members of a street gang.

Several patterns emerge from the visual representation of this network component in figure 3. First, focusing in on the largest component reveals that clustering also occurs *within* a network: One can easily see dense pockets of individuals connected to each other through a small number of ties. Second, many clusters in the largest component do not experience a single shooting. For instance, clusters in the center and top center of the graph have several clusters without a single shooting victim. Clearly, then, not all clusters in the network are equal with respect to exposure to gun violence.

Figure 3. Largest Component with Fatal and Nonfatal Gunshot Victims (darker nodes)



PREDICTING GUNSHOT VICTIMIZATION

Table 4 presents the results of our logistic regression models of any individual's risk of nonfatal or fatal gunshot victimization.[9] Two hundred individuals in the network lacked

9. We also estimated random-effects models that allowed the slopes and intercepts for network cluster membership to vary, where the level 2 units were the network component. These models produced nearly identical findings when compared with results of the models presented here; in fact, a test of the difference of log-likelihood between the models presented here and the models including random effects for network cluster are nearly identical. The likelihood ratio test of the logistic regression versus random effects model yields a chibar of zero, indicating virtually no difference between standard logistic regression models and random-effects models.

Table 4. Logistic Regressions Predicting Individual Victimization with Individual and Network Variables

	Model 1		Model 2		Model 3	
Variables	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
Individual Variables						
Age (mean centered)	1.053***	(1.032 – 1.075)	1.051***	(1.028 – 1.072)	1.049***	(1.029 – 1.073)
Black (1 = yes, 0 = no)	5.955***	(2.599 – 13.644)	5.564***	(2.413 – 12.828)	5.291***	(2.299 – 12.208)
Gender (1 = male, 0 = female)	5.253***	(1.922 – 14.359)	4.946***	(1.807 – 13.532)	4.993*	(1.827 – 13.667)
Gang member (1 = yes, 0 = no)	4.439***	(3.025 – 6.514)	5.545***	(3.527 – 8.718)	5.445***	(3.466 – 8.566)
Network Variables						
Degree			1.037	(.965 – 1.115)		
Ego-density			.771	(.504 – 1.180)	.762	(.497 – 1.169)
Cluster size			1.001	(.999 – 1.000)	1.001	(.998 – 1.001)
Closeness to gang member (minimum)			1.945*	(1.106 – 3.421)	1.921**	(1.083 – 3.307)
N of arrests					1.136†	(.971 – 1.321)
N of field interrogation contacts					1.054	(.978 – 1.146)
N quality-of-life calls					.971	(.863 – 1.092)
Constant	.0003***	(.000 – .001)	.0003***	(.000 – .001)	.0003***	(.000 – .001)
Log Likelihood	–580.013		–574.647		–573.060	
N	10,531		10,531		10,531	

†$p < .10$; *$p < .05$; **$p < .01$; ***$p < .001$.

complete data on all of the relevant individual variables, leaving a final sample size of $N = 10{,}531$. All models were estimated with Stata 12.0 statistical software (StataCorp, 2011).

Model 1 presents the odds ratios of our baseline regression with only the individual-level predictors: age, race, gender, and gang membership. Consistent with prior research, being Black and male increases one's odds of being a gunshot victim in Newark. The probability of victimization also increases with mean-centered age. The magnitude and significance of these parameters is consistent across all models. Also consistent with prior research, the effect of gang membership on individual victimization is large. In model 1, for example, being a gang member in the network increases one's odds of also being a victim approximately 344 percent (odds ratio [OR] = 4.439, $p < .001$) when holding all other variables constant.

Model 2 lists the odds ratios from a logistic regression that adds the network variables and our main theoretical variable to the baseline model. Degree centrality and cluster size have a positive association with victimization and ego-density has a negative association, but none of these variables attain statistical significance in model 2 or any subsequent models. Although these parameters are nonsignificant, we control for these network attributes as potential confounding variables as a source of spuriousness.

In support of our main hypothesis, the closeness parameter in model 2 is positive and statistically significant (OR = 1.945, $p < .05$), indicating that one's probability of being a victim of a fatal or nonfatal gunshot injury in Newark increases the closer one is to a gang member. Conversely, the further away one is from a gang member, it becomes less likely that he or she will be the victim of a gunshot injury. Linking back to the shooting vignette that introduced this article, Greg, the known member of the G-Shines, might have been expected to have an elevated probability of victimization—indeed, our model 1 suggests that gang membership in Newark increases one's odd of gunshot victimization by roughly 344 percent, net of other individual characteristics. Accordingly to model 2, Tony's odds of being a gunshot victim increase 94 percent simply by being connected to Greg. Thus, being in a network with gang members—and more than that, being *closer* to gang members in the network—significantly increases the probability of gunshot victimization.

Unfortunately, as we described, our current data do not allow us to account directly for individual selection into our network or for individual criminal propensity and any potential confounding of such propensity with our closeness to gang measure. Partly as a way to address this issue given the available data, model 3 adds a series of variables of the count of the number of arrests (mean = .52; standard deviation [SD] = .916; min-max = 0–10), FIs (mean = 1.32; SD = 1.980; min-max = 0–28), and QOL (mean = .871; SD = 1.902; min-max = 0–38) contacts for each individual during the study time period. Degree is dropped in the model because of its high bivariate correlation with the number of FI and QOL reports (Pearson's $r = .797$ and .693, respectively). The magnitude, direction, and significance of all variables remain nearly identical to those found in model 2—including the closeness to gang member parameter—thus providing additional support as to the robustness of our findings. When considering these three count variables, only the number of arrests (OR = 1.136, $p < .10$) achieves even the most lax level of statistical significance.

As a sensitivity analysis, we also ran a series of logistic regression models for the subnetworks generated by each tie type and possible combinations therein. Subsuming the entire network by tie type, however, affects all network variables (including density, cluster size, and degree) because it breaks the larger network into a greater number of components

and, in so doing, affects these other structural properties. Nonetheless, the results from these additional analyses were consistent with the findings presented in our main analysis. The closeness parameter in the FI only network was OR = 2.05 (confidence interval [CI] = .999 – 4.078, $p < .05$) and the arrest-only network was OR = 1.74 (CI = 1.122 – 2.361, $p < .01$). The closeness parameter in the QOL-only network achieved statistical significance at a less restrictive level (OR = 2.171, CI = .728 – 5.471, $p < .10$), however.

DISCUSSION AND CONCLUSION

This study analyzed one way that violence might be transmitted outward from at-risk populations—gang members—to their nongang co-offending associates. In the real-world example that began this article, this means understanding how the social connections between associates—like Tony and Greg—might influence one's probability of becoming a shooting victim. We hypothesized that violence might spill over from gang members to nongang members within such networks, specifically through co-offending connections that might expose nongang members to additional risky situations, behaviors, and people. By using police data, we recreated the co-offending network for the entire city of Newark for a 12-month period, locating more than 10,000 unique individuals in this network. A descriptive analysis confirmed the concentration of gun violence: Nearly one third of all shooting victims could be located in a network containing less than 4 percent of the city's population. Regression analyses confirmed our central hypothesis: Those who are closer to gang members in their co-offending network are at an elevated risk for victimization. Our "closeness to gang member" measure suggests that being directly connected to a gang member increases a nongang associate's probability of being shot by 94 percent.

The study has several limitations. First, as mentioned, our study is circumscribed by all the usual caveats associated with the use of official police data in criminological research, such as bias introduced by police decision-making processes (Black, 1970). Second, despite our expanded use of data beyond arrest records, we still most likely underestimate measures of the "true" social network by missing 1) individuals who are not represented in the data and 2) ties among people both in and out of the data that are not captured in the data. In short, although we capture a sizeable network and a great number of all gang members and shooting victims, our estimates are most likely conservative. Third, our reliance on police-defined gang membership may overestimate or underestimate the true extent of gang membership in Newark. Although this cannot be confirmed without additional nonpolice data, we believe our estimates are fairly accurate because they represent similar estimates of gang membership in networks from other cities (e.g., Papachristos and Wildeman, 2014) as well as the fact that previous research has demonstrated the construct validity of police-defined measures of gang membership (Decker and Pyrooz, 2010).

Finally, our study cannot address directly how selection into these co-offending networks or the extent to which one's "closeness to a gang member" is confounded with general criminal propensity. Namely, more violent or otherwise criminal-prone individuals might be more likely to form co-offending ties in the first place, one of the key positions of self-control theory, or they might be more likely to have gang associates (e.g., Gottfredson and Hirschi, 1990). Even though we lack individual-level data to address these issues

directly, our main findings hold across models that control for any individual's level of criminal involvement during the observation period (model 3). Although not directly measuring individual selection into co-offending networks or having gang associates, such an interpretation would be consistent with recent work by Young (2011), who found no evidence that self-control–related variables are related to friendship formation in adolescent networks. Future research should consider additional ways that data might be leveraged to understand such selection processes more clearly.

Limitations notwithstanding, our findings have several important implications for future research and our understanding of gun violence more broadly. First, our network analysis clearly demonstrates that the boundaries of gangs are far from rigid: Nearly all the gangs in our study could be located in a single network connected to each other directly or indirectly through co-offending links among individuals. Through such networks, the effects of gang membership extend outward from gang members, like Greg, to influence the victimization patterns of nongang members, like Tony. As such, the second contribution of this study is its demonstration that the effects of gang membership extend beyond the world of gang members, which provides evidence that such patterning is correlated with co-offending networks. Third, by analyzing a network for the entire city of Newark, our study was one of the first to examine variation in such networks and, therefore, suggests that results from earlier studies taken from snowball samples or single communities could hold true for entire cities.

Finally, the fact that patterns of violence victimization are both concentrated in social networks *and* influenced by the distribution of risk factors within such networks (i.e., gang membership) advances our understanding of the ways that gun violence might be considered a social "epidemic." Research on crime epidemics, including the recent Newark study by Zeoli et al. (2014), has demonstrated that the spatial and temporal patterning of violence follows epidemic-like diffusion patterns, often spreading outward from areas with high concentrations of gangs and guns. Others have postulated that gangs play a crucial role in such an epidemic-like process by acting as carriers and transmitters of violence within their own communities as well as to other communities in which the gang or its members might travel (Brantingham et al., 2012; Cohen et al., 1998; Papachristos, Hureau, and Braga, 2013). The current study takes one important step in expanding this line of thinking by demonstrating the avenues through which individual acts of violence might spread—through quantifiable social networks that can be readily measured using existing police data. We have long known that gun violence is not randomly distributed across places or within populations. Yet our actual measurement of the avenue of transmission—the actual structure of the networks across which influence might travel—has been limited.

As a growing number of scholars begin to understand the diffusion of violence as a public health epidemic and to equate the contagion of violence akin to other infectious diseases, the current study suggests that violence most likely travels, not randomly, but along tangible social networks. In other words, if violence is a disease, then it is perhaps more like a blood-borne pathogen that is transmitted through precise types of behaviors and interpersonal contact than it is like an airborne pathogen that can spread through broad and less personal contacts. Tragic stray bullet killings do occur, but violence is transmitted largely through specific interactions and connections within social networks. The company you keep either protects you from or makes you more vulnerable to becoming a victim of assaultive gun violence.

REFERENCES

adams, jimi, James Moody, and Martina Morris. 2013. Sex, drugs, and race: How behaviors differentially contribute to the sexually transmitted infection risk network structure. *American Journal of Public Health* 103:322–9.

Battin, Sara R., Karl G. Hill, Robert D. Abbott, Richard F. Catalano, and J. David Hawkins. 1998. The contribution of gang membership to delinquency beyond delinquent friends. *Criminology* 36:93–116.

Bearman, Peter S., James Moody, and Katherine Stovel. 2004. Chains of affection: The structure of adolescent social networks. *American Journal of Sociology* 110: 44–91.

Black, Donald J. 1970. The production of crime rates. *American Sociological Review* 35:733–48.

Bouchard, Martin, and Richard Konarski. 2014. Assessing the core membership of a youth gang from its co-offending network. In *Crime and Networks*, ed. Carlo Morselli. New York: Routledge.

Brantingham, P. Jeffrey, George E. Tita, Martin B. Short, and Shannon E. Reid. 2012. The ecology of gang territorial boundaries. *Criminology* 50:851–85.

Bursik, Robert J. 1999. The informal control of crime through neighborhood networks. *Sociological Focus* 32:85–97.

Burt, Ronald S. 1987. Social contagion and innovation: Cohesion versus structural equivalence. *American Journal of Sociology* 92:1287–335.

Christakis, Nicholas A., and James H. Fowler. 2007. The spread of obesity in a large social network over 32 years. *New England Journal of Medicine* 357:370–9.

Christakis, Nicholas A., and James H. Fowler. 2008. The collective dynamics of smoking in a large social network. *The New England Journal of Medicine* 358:2249–58.

Cohen, Jacqueline, Daniel Cork, John Engberg, and George Tita. 1998. The role of drug markets and gangs in local homicide rates. *Homicide Studies* 2:241–62.

Csardi, Gabor, and Tamas Nepusz. 2006. The igraph software package for complex network research. *InterJournal* Complex Systems: 1695.

Decker, Scott H. 1996. Collective and normative features of gang violence. *Justice Quarterly* 13:243–64.

Decker, Scott H., Charles M. Katz, and Vincent J. Webb. 2007. Understanding the black box of gang organization: Implications for involvement in violent crime, drug sales, and violent victimization. *Crime & Delinquency* 54:153–72.

Decker, Scott H., and David C. Pyrooz. 2010. On the validity and reliability of gang homicide: A comparison of disparate sources. *Homicide Studies* 14:359–76.

Esbensen, Finn-Aage, and David Huizinga. 1993. Gangs, drugs, and delinquency in a survey of urban youth. *Criminology* 31:565–89.

Fagan, Jeffrey. 1989. The social organization of drug use and drug dealing among urban gangs. *Criminology* 27:633–70.

Fleisher, Mark S. 1998. *Dead End Kids: Gang Girls and the Boys They Know*. Madison: University of Wisconsin Press.

Fleisher, Mark S. 2006. Youth gang social dynamics and social network analysis: Applying degree centrality measures to assess the nature of gang boundaries. In *Studying Youth Gangs*, eds. James F. Short, Jr. and Lorine A. Hughes. Lanham, MD: Alta Mira.

Fowler, James H., and Nicholas A. Christakis. 2008. Dynamic spread of happiness in a large social network: Longitudinal analysis over 20 years in the Framingham Heart Study. *British Medical Journal* 337:1–9.

Garot, Robert. 2010. *Who You Claim? Performing Gang Identity in School and on the Streets*. Princeton, NJ: Princeton University Press.

Gilman, Amanda B., Karl G. Hill, and J. David Hawkins. 2014. Long-term consequences of adolescent gang membership for adult functioning. *American Journal of Public Health* 104:938–45.

Gordon, Rachel A., Benjamin B. Lahey, Eriko Kawai, Rolf Loeber, Magda Stouthamer-Loeber, and David P. Farrington. 2004. Antisocial behavior and youth gang membership: Selection and socialization. *Criminology* 42:55–88.

Gottfredson, Michael R., and Travis Hirschi. 1990. *A General Theory of Crime*. Stanford, CA: Stanford University Press.

Harding, David J. 2010. *Living the Drama: Community, Conflict, and Culture among Inner-City Boys*. Chicago, IL: University of Chicago Press.

Harper, Gary W., and W. LaVome Robinson. 1999. Pathways to risk among inner-city African-American adolescent females: The influence of gang membership. *American Journal of Community Psychology* 27:383–404.

Harper, Samuel, John Lynch, Scott Burris, and Goerge D. Smith. 2007. Trends in the black-white life expectancy gap in the United States, 1983–2003. *Journal of the American Medical Association* 297:1224–32.

Haynie, Dana L. 2001. Delinquent peers revisited: Does network structure matter? *American Journal of Sociology* 106:1013–57.

Hughes, Lorine A. 2013. Group cohesiveness, gang membership prestige, and delinquency and violence in Chicago, 1959–1962. *Criminology* 51:795–832.

Kadushin, Charles. 2012. *Understanding Social Networks: Theories, Concepts, and Findings*. New York: Oxford University Press.

Kennedy, David M., Anthony A. Braga, and Anne. M. Piehl. 1997. The (un)known universe: Mapping gangs and gang violence in Boston. In *Crime Mapping and Crime Prevention*, eds. David L. Weisburd and Tom McEwen. Monsey, NY: Criminal Justice Press.

Klofas, John, and Natalie K. Hipple. 2006. Prokect safe neighborhoods: Strategic interventions. *Crime Incident Reviews: Case Study 3*. Washington, DC: U.S. Department of Justice.

Koester, Stephen, Jason Glanz, and Anna Baron. 2005. Drug sharing among heroin networks: Implications for HIV and hepatitis B and C prevention. *AIDS and Behavior* 9:27–39.

Kreager, Derek A., Kelly Rulison, and James Moody. 2011. Delinquency and the structure of adolescent peer groups. *Criminology* 49:95–127.

Malm, Aili, Gisela Bichler, and Stephanie Van De Walle. 2010. Comparing the ties that bind criminal networks: Is blood thicker than water? *Security Journal* 23: 52–74.

Marsden, Peter V. 2002. Egocentric and sociocentric measures of network centrality. *Social Networks* 24:407–23.

Marsden, Peter V., and Noah E. Friedkin. 1993. Network studies of social influence. *Sociological Methods & Research* 22:127–51.

Matsueda, Ross L. 1982. Testing control theory and differential association: A causal modeling approach. *American Sociological Review* 47:489–504.

McGloin, Jean M. 2005. Policy and intervention considerations of a network analysis of street gangs. *Criminology & Public Policy* 4:607–36.

McGloin, Jean M., and Holly Nguyen. 2014. The importance of studying co-offending networks for crimionology theory and policy. In *Crime and Networks*, ed. Carlo Morselli. New York: Routledge.

McGloin, Jean M., and Alex R. Piquero. 2010. On the relationship between co-offending network redundancy and offending versatility. *Journal of Research in Crime and Delinquency* 47:63–90.

Morselli, Carlo. 2009. *Inside Criminal Networks*. New York: Springer.

National Gang Center. n.d. Gang-related legislation by state. New Jersey. https://www.nationalgangcenter.gov/Legislation/New-Jersey.

Papachristos, Andrew V. 2006. Social network analysis and gang research: Theory and methods. In *Studying Youth Gangs*, eds. James F. Short and Lorine A. Hughes. Lanham, MD: AltaMira Press.

Papachristos, Andrew V. 2011. The coming of a networked criminology? In *Measuring Crime & Criminality: Advances in Criminological Theory*, ed. John MacDonald. New Brunswick, NJ: Transaction.

Papachristos, Andrew V., Anthony A Braga, and David Hureau. 2012. Social networks and the risk of gunshot injury. *Journal of Urban Health* 89:992–1003.

Papachristos, Andrew V., David M. Hureau, and Anthony A. Braga. 2013. The corner and the crew: The influence of geography and social networks on gang violence. *American Sociological Review* 78:417–47.

Papachristos, Andrew V., and Christopher Wildeman. 2014. Network exposure and homicide victimization in an African American community. *American Journal of Public Health* 104:143–50.

Payne, Danielle C., and Benjamin Cornwell. 2007. Reconsidering peer influences on delinquency: Do less proximate contacts matter? *Journal of Quantitative Criminology* 23:127–49.

Peterson, Dana, Terrance Taylor, and Finn-Aage Esbensen. 2004. Gang membership and violent victimization. *Justice Quarterly* 21:793–815.

Pizarro, John, and Jean McGloin. 2006. Gang homicides in Newark: Collective behavior or social disorganization? *Journal of Criminal Justice* 34:195–207.

Pyrooz, David C. 2014. From colors and guns to caps and gowns? The effects of gang membership on educational attainment. *Journal of Research in Crime and Delinquency* 51:56–87.

Pyrooz, David C., Richard K. Moule, Jr., and Scott H. Decker. 2014. The contribution of gang membership to the victim–offender overlap. *Journal of Research in Crime and Delinquency* 51:315–48.

Pyrooz, David C., Gary Sweeten, and Alex R. Piquero. 2013. Continuity and change in gang membership and gang embeddedness. *Journal of Research in Crime and Delinquency* 50:272–99.

R Core Team. 2014. *R: A Language and Environment for Statsitical Computing*. Austria: R Foundation for Statistical Computing. http://www.R-project.org.

Rosenquist, James N., James H. Fowler, and Nicholas A. Christakis. 2011. Social network determinants of depression. *Molecular Psychiatry* 16:273–81.

Sampson, Robert J. 2012. *Great American City: Chicago and the Enduring Neighborhood Effect*. Chicago, IL: University of Chicago Press.

Sierra-Arevalo, Michael, and Andrew V. Papachristos. 2015. Networks, gangs, and gang research. In *Handbook of Gangs and Gang Responses*, eds. David C. Pyrooz and Scott H. Decker. New York: Wiley.

Spano, Richard, Joshua D. Freilich, and John Bolland. 2008. Gang membership, gun carrying, and employment: Applying routine activities theory to explain violent victimization among inner city, minority youth living in extreme poverty. *Justice Quarterly* 25:381–410.

StataCorp. 2011. *Stata Statistical Software: Release 12*. College Station, TX: StataCorp LP.

Sutherland, Edwin H. 1947. *Principles of Criminology*, 4th ed. Philadephia, PA: J.B. Lippincott.

Thornberry, Terence P. 1998. Membership in youth gangs and involvement in serious and violent offending. In *Serious and Violent Offenders: Risk Factors and Successful Interventions*, eds. Rolph Loeber and David P. Farrington. Thousand Oaks, CA: Sage.

Thornberry, Terence P., Marvin D. Krohn, Alan J. Lizotte, Carolyn A. Smith, and Kimberly Tobin. 2003. *Gangs and Delinquency in Development Perspective*. New York: Oxford University Press.

U.S. Census Bureau. 2015. State and country quickfacts. Newark (city), New Jersey. http://quickfacts.census.gov/qfd/states/34/3451000.html.

U.S. Department of Justice. 2012. *Crime in the United States*. Federal Bureau of Investigation. https://www.fbi.gov/about-us/cjis/ucr/crime-in-the-u.s/2012/crime-in-the-u.s.-2012/tables/8tabledatadecpdf/table-8-state-cuts/table_8_offenses_known_to_law_enforcement_by_new_jersey_by_city_2012.xls

Valente, Thomas W. 2010. *Social Networks and Health: Models, Methods, and Applications*. New York: Oxford University Press.

Warr, Mark. 2002. *Companions in Crime: The Social Aspects of Criminal Conduct*. New York: Cambridge University Press.

Wasserman, Stanley, and Katherine Faust. 1994. *Social Network Analysis: Methods and Applications*. Cambridge, U.K.: Cambridge University Press.

Young, Jacob T. N. 2011. How do they "end up together"? A social network analysis of self-control, homophily, and adolescent relationships. *Journal of Quantitative Criminology* 27:251–73.

Zeoli, April M., Jesenia M. Pizzaro, Sue C. Grady, and Christopher Melde. 2014. Homicide as an infectious disease: Using public health methods to investigate the diffusion of homicide. *Justice Quarterly* 31:609–32.

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